Farmer Assisted Mobile Framework for Improving Agricultural Products

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Abstract. Agricultural products are vital to the survival of man and in its larger scale of production could contribute to the economy of a nation. Farmers who are at the fore front of Agriculture are faced with several challenges. This paper identifies some of the challenges and in particular focuses on leaf diseases that affect crops. A disease if not well addressed could destroy crops and hence a loss in investment. Using contemporary technology that is affordable and portable, such as mobile devices, this paper develops a framework through which intervention by an expert system on crop diseases could be implemented.

Keywords: Crop, disease, mobile device, farmer, service oriented architecture.

1 Introduction

A bumper harvest in general could suggest that there is a reasonable amount of Agricultural products' availability, the benefit of which would mean affordability and hunger alleviation. However in the event of poor harvest which implies low yield, would result into high prices of products and affordability becomes problematic. Hence there is the need to address the causes of low yield. One of such causes is leaf disease, which affects both the level of yield and the quality of crop. Although there is established plant disease control measures [1], farmers need to be knowledgeable in determining which one to apply and how to apply it. Another challenge is the awareness of where to purchase required treatment spray. Most importantly the defining route to success is in identifying what disease it is otherwise ultimately the wrong spray will be applied to the crop in question. Usually an expert will be consulted when a farmer suspects anomaly regarding his or her crop. The cost of consultancy especially to medium and low scale farmers could be expensive which could also indirectly affect the level of crop yield.

The use of information and communication technology (ICT) could be employed in providing expert advice on issues related to Agriculture, and in particular addressing leaf diseases. One of suitable technology is mobile devices such as smartphones.

The use of mobile phones has significantly increased across Africa as many people have embraced this communication technology. According to the ITU [2], in 2004, Africa was the world's fastest-growing mobile phone market. There are now more mobile phones in some African countries than there are landlines [3]. According to CCS Insight [4], the shipment of smartphones is on the increase and the Sales of smartphones have been helped by new, cheaper devices, especially, but not only, in emerging markets. The mobile phone has become the driving force for globalization in Africa and it is being used even where there is no power network as villagers have devised a means of using car battery to charge phones, additionally majority of Africans now own a mobile phone and a second revolution hitting the continent is internet access [5].

Hence, the availability of mobile phones and internet access provides an enabling platform through which people in rural areas could be reached. For instance farmers could be assisted through the use of mobile application (app) to address several of problems related to crop yield. One of such problems is crop disease. This paper focuses on establishing a framework that could be used to develop a mobile app that can assist farmers in diagnosing and identifying the disease, and to proffer intervention measures. Thus the reminder of this paper is structured as follows. Section 2 discusses leaf disease and control measures. Section 3 discusses a service oriented architecture on which the proposed framework in this paper is founded. In section 4 we discuss imaging as used in the diagnosis of leaf disease. Section 5 presents the developed farmer assisted mobile framework, and finally we draw conclusions in section 6.

2 Leaf Disease Control and Management

Over the stages of annual growth cycle, plants might be attacked by several types of pests and, bacterial and fungal diseases. Hence, professional agricultural knowledge and expertise is a prerequisite for diseases management and control and eventually for good yield. For farmers who are working in far rural areas, a mobile application could be the best suggestion to facilitate the right on time availability of such knowledge and expertise. The role of the suggested app is defined by the delivery of four tasks: (a) scheduling jobs and procedures towards healthy growing, (b) prioritising diseases' symptoms for early detections; (c) diagnosing symptoms and their likely causes, and (d) prescribing effective treatment procedures [6]. The technical implementation of the app is moreover from three constituents: a knowledgebase, a management and control algorithm and a connection to Internet of Things (IoT).

Informed by the modelled agricultural knowledge and expertise of the knowledgebase, the algorithm considers the growth cycle and given weather conditions and accordingly delivers the aforementioned four tasks. Up-to-date weather conditions are drawn continuously from IoT (i.e. Meteorological Station Network) and hence the algorithm can adjust the proper timings to plan normal agricultural and/or diseases treatment procedures. To facilitate clear understanding of the implementation process of the app, table grape plants is considered as a case study throughout this section.

2.1 Knowledgebase of Control and Management

Building up a thorough and effective knowledgebase may require extending the modelling consideration from pre-planting conditions to others that include present weather and health conditions. For grapevine, pre-planting conditions may have several impacts on the quality of the crop and the appearance and severity of symptoms of diseases. Among those conditions are: site selection, elevation, direction of slope, site development and soil testing. Specifically, vineyard sites that are close to wild grapevines are most likely to be attacked by certain types of pests. Similarly, elevation and direction of slope have impact on the exposure of the vineyard to extended wet or dry time and trunk injury from winter cold. Hence, as a provision for some of these exposures, heaters or wind circulator should be used at proper timings. Soil test, moreover, could identify the mineral imbalance, environmental pollution and a number of non-biotic disease reasons and from there the effective management and control programme can be decided. Such programme may incorporate fertiliser and/or schedule of application of organically approved pesticides or biocontrol agents [7, 8].

Beyond that, the incorporation of the pre-planting conditions could support probabilistic reasoning of the control and management algorithm. Along with each stage of the growing cycle of plants, a prioritised list of diseases can be presented – arranged in terms of probability, from the highest to the lowest. For each disease moreover, observable symptoms are identified and then upon the confirmation of the occurrence of a symptom the proper treatment procedure would be prescribed by the algorithm. To model interrelated relations among life-cycle stages, diseases, symptoms, agricultural tasks and treatment procedures, UML state-machine could be the best abstraction. Fig. 1 shows a simplified state-machine of the annual growth cycle of grapevines [9]. Each state (rounded rectangles) of the model represents a growth stage and each arrow represents a trigger event that causes a transition from a stage to its subsequent one.

Fig. 1. Annual growth cycle of grapevines

In order for the model to facilitate effective holding of thorough knowledge, each state is divided further into sub-states. Each sub-state could be triggered by health conditions of the current stage (state) of growth cycle or conditions that have been observed during former stage or season. Fig. 2 shows the sub-states of bud break state (state 2 of Fig. 1) [10].

The bud break state is triggered when the buds appear expanded and pruned vines start bleeding. At the top of the left-hand side of the state (Fig. 2), it could be seen that the state encloses recommendations attribute, which may (or not) incorporate recommended actions to be taken by the farmer. Assuming that there was an outbreak of

Fig. 2. Bud break state and enclosed sub-states

powdery mildew during a growth stage of last season, the trigger event of the bud break state is associated with 1.1. This association reflects the sub-state number which corresponds to outbreak conditions during the former state – dormancy state. Powdery Mildew is a fungal disease that may attack grapevine over several growth stages; bud break, pre-bloom, 1st, 2nd, 3rd and 4th cover stages, preharvest and postharvest.

At this stage and as there was an outbreak during last season, sub-state 2.1 (Fig. 2) is triggered and its enclosed action should be taken. As shown by sub-state 2.1, fungicides that have been used during last season and the given weather conditions should be considered. Assuming that sulphur has been used as a fungicides or the temperature is below 65°F or above 90°F, so it is recommended to use any of the following new fungicides material: Abound, Sovran, Flint and Pristine. After applying that action, two more symptoms are prioritised according to weather conditions. More specifically, if the last winter was cool and wet then observed symptom of dark brown spots of size 2 to 3 mm would suggest phomopsis (a fungal disease) infection. In different case, if the given weather is mild then observed symptom of whitish or greenish-white powdery patches on leaves would suggest powdery mildew.

If there was no outbreak of powdery mildew, those two symptoms should be prioritised and observed immediately after triggering the bud break state. Throughout the growth cycle, the emergence of inflorescences, during bud break stage, triggers pre-bloom stages. Assuming that there was a fungal infection of phomopsis then the trigger event (inflorescences emerging) is associated with the number of the correspondent sub-state (2.2). In such a case, if there are any further actions to be taken during the pre-bloom stage, the proper sub-state is triggered and actions are presented to the farmer. This mechanism is applied over all the annual life cycle to maintain consistent record across consecutive stages throughout every season. The degree of susceptibility to a disease might vary from grapevine to another. For example, vine such as Carignane, Thompson Seedless, Ruby Seedless, Cardinal, Chardonnay, Cabernet Sauvignon and Chenin blanc are likely to be affected by Powdery (or downy) mildew fungal infection. Others like White Petite Sirah, Zinfandel, Semillon, and

White Riesling are less susceptible. Identifying the type of the grapevines and their susceptibility would support the reasoning of the control and management algorithm to achieve more effective focus and prioritisation of symptoms [11]. Photos are organised across life-cycle stages (states and sub-states) to show examples of symptom detection of former season and possible infections.

2.2 Control and Management Algorithm

For effective reasoning of the control and management algorithm, initial settings of poor soil minerals, regional area and the type of the grapevine are required. Identifying poor minerals would allow the algorithm to schedule enrichment program to apply the required fertilisers across the annual life cycle. Knowledge about the lack of minerals can also be incorporated in the sub-states throughout the life cycle states. Alike, regional and grapevine type settings could support identifying the corresponding weather conditions and then prioritising observable symptoms and scheduling and other agricultural practice.

Drawing from the information enclosed by each state of the annual cycle, the algorithm tells the farmers about the recommended actions that should be taken. If moreover there was an infection during the former season or life stage then actions that complete the required treatment procedure are prescribed. According to the given weather conditions associated with each trigger event the algorithm prioritises list of symptoms and presents them to the farmer to investigate them. Once a symptom is detected and verified, the algorithm achieves state transition to the correspondent sub-state and from there identify the name of the disease and the required treatment procedure (see Fig. 2).

The algorithm can draw also information from the recent applications such as those of smart architecture, which has been standardised and brought to use by the IoT. That exploitation can come up with more effective control and management procedures. For example, the deployment of wireless sensors that can monitor soil moisture and trunk diameter in vineyards will result eventually in controlling the amount of sugar in grapes and grapevine health (e.g. wine quality enhancing). Similarly, a link and access to the Meteorological Station Network could help algorithm to consider weather forecast, adapted to the predictable conditions and plan agricultural or treatment procedures more effectively [12, 13].

3 Role of Imaging in the Diagnosis of Leaf Disease

Modern leaf disease diagnosis employs the use of technology aided by advanced research in Computer vision. Although this is still a challenge despite research efforts over a number of years, the advancement reached so far has been helpful in solving crop diseases. Typically leaf disease diagnosis relies on necked eye observation by experts. This is very expensive, time consuming and could be cumbersome especially where large tracts of land are involved. Therefore, the use of technology for such

purposes becomes necessary. A lot of research on the application of computer image processing technology in agriculture has been carried out by various scholars. However, it is important to note that of these studies few are on diagnosis of crop diseases and the recognition technology for leaf diseases are even fewer [14].

According to Zhu et.al [14] leaf diseases are automatically recognised by digital image processing techniques and pattern recognition method. Their work was separated into three steps which are: (i) image acquisition and pre-processing, (ii) segmentation of disease spots from leaves using iterative threshold method and morphological methods, and (iii) shape characteristics parameters of disease spots are extracted and used to identify and diagnose diseases. The results of their method gave a success rate of 80%. Dhaygude and Kumbhar [15] used texture statistics for the detection of plant leaf disease. Their method involved colour transformation structure - Red Green Blue (RGB) to Hue Saturation Value (HSV), masking and removing green pixels using pre-computed threshold value, segmentation is carried out for the analysis of texture using co-occurrence matrix. Texture parameters of diseased and normal leaf are compared. The method could be improved by applying neural networks to increase the recognition rate of the classifier.

Jin et al. [16] proposed a method that combines image processing and artificial neural network technology. The method used division algorithm and the computation of eigen values. The values are fed into a three level neural network model to identify the diseased spot areas. New methods for diagnosis of soybean leaf disease that are deployed for remote diagnosis are explored. These are based on geometric, colour and texture features. Kulkarni and Patil [17] proposed a method for early and accurate detection of plant diseases using diverse image processing techniques and artificial neural network (ANN). Their disease detection system involved image capturing, filtering and segmentation using gabor filter, extraction of texture and colour features. ANN is trained by using feature values that distinguishes healthy and diseased samples. The evaluation of their technique showed a 91% recognition rate. The technique suggests a breakthrough in the search for an accurate machine vision system that can be deployed for recognition and classification of plant diseases.

Bashir and Sharma [18] observe that relying on pure naked-eye observation to detect and classify diseases can be imprecise and cumbersome. Instead they presented an effective approach for detection of diseases in *Malus Domestica* using methods like K-means clustering, colour and texture analysis. The approach though could be improved by using statistical methods like the Bayes and Principal Component Analysis (PCA) for classification. Marathe and Kothe [19] calculated infected area in percentage by subtracting total green leaf area from total leaf area. They used MATLAB instructions for the image pre-processing, enhancement and the calculations. Their algorithm is mainly based on the presence of holes and the change of colour of the leaf.

Landge et al [20] classified Stem Borer attack and Brown stripe downy mildew disease on a plant of maize. Their method involved colour transformation from RGB images to HSI. This is followed by masking green pixels and removal of masked cells. These are then used to generate a binary matrix which is transferred into a neural network for classification. The algorithm could be improved by applying genetic

algorithms and neural networks that would increase the recognition rate and the severity of the disease.

The framework for any vision related system for image classification is the same and can be adapted from one environment and or context to another with little effort. Digital images are acquired from the environment using digital cameras. The images are pre-processed to remove noise under which they are taken and enhanced. Image segmentation is used to extract important features for further analysis. Several techniques are then used to classify the images according to the problem at hand. Research in this area now calls for improvements on the accuracy of the system in the diagnosis, classification and prediction of the severity rate.

4 Service Oriented Architecture

To assist a farmer through mobile app would imply that the mobile app will remotely access a service. This is advantageous in the sense that several farmers could remotely access the service at same time compared to each farmer having a standalone version of the service. Hence, one could say that this approach is also cost-effective. This section presents an overview of service oriented architecture (SOA).

Service oriented architecture is a way of developing distributed systems where the system components are standalone services, executing on geographically distributed computers [21]. This implies that the service clients (devices which access the service and will henceforth be referred to as client) could exist at different locations on the globe. SOA involves communication between clients and the service. XML based protocols such as SOAP (simple object access protocol) and WSDL (web service description language) have been developed to support communications between clients and service. Services are platform independent and the good news to a programmer is that their access is language independent. One other good news is that services can be discovered either through features provided by and IDE (integrated development environment) or search engine. Overview models of service oriented architecture are shown in Fig. 3 and Fig. 4. Fig. 3 is a basic model while Fig. 4 is a more detailed model.

Fig. 3. A basic service oriented model

The client in Fig. 3 performs a request or a remote method invocation via a public interface of accessible methods provided by the service. The service then processes the request and sends the result to the client as indicated by service response in Fig. 3. However, a service can also remotely invoke the method of other services, and a client could remotely invoke methods from different services. This scenario is depicted in Fig. 4 where ‘A’ is a request and ‘B’ a response.

Fig. 4. A more detailed service oriented model

5 Farmer Assisted Mobile Framework

Current approaches to assisting farmers involve a visit by Agricultural extension officer. This may not be regular and sometimes the farmer may have to look for such personnel. More so, the Agricultural extension officer may not be able to provide feedback to the farmer immediately. This would mean waiting for days in order to get feedback. This delay could be costly as the conditions of crop may deteriorate further leading to a situation that is difficult to control. Hence some form of automation to assisting farmers would be helpful.

Having investigated how leaf disease could be controlled and how imaging could be used in the diagnosis of the disease, the control measure is then informed. It is therefore plausible to develop a framework which could be used in developing farmer assisted mobile applications. This framework is as shown in Fig. 5. The picture of a suspected leaf is taken using the mobile device, certain environmental conditions such as weather, elevation, etc at the farm location are also record. Such parameters are obtained through services available from IoT. The IoT may also rely on services from a satellite as seen in the figure. In order to promote transparency in the framework, the farmer only needs to take the picture using the mobile app and send it for diagnosis and waits for the results. The only interface between the farmer's mobile device and the expert system (the knowledgebase, management and control system) is the service interface. Once the set of inputs are received from the farmer, the service interface passes this to the management and control algorithm (MCA) where the analysis takes place. In performing the analysis, the MCA communicates with the knowledgebase (KB) which is a repository of information regarding healthy and unhealthy conditions of agricultural plants.

Fig. 5. Farmer assisted mobile framework

6 Conclusions

Rural farmers may usually have to travel a long distance to obtain services regarding their farm products. Some of the required services could be an advice on how to apply fertilizer, advice on how to treat a particular leaf disease or referral, etc. This paper has developed a framework through which a mobile application could be developed to improving farmers' accessibility to information that could boost production. The developed framework is a distributed system that is based on service oriented architecture. Further work will be required in the following areas:

- use the framework to develop a detailed architecture of the service,
- identify a site in Namibia which could be used as case study,
- identify a mobile device and platform on which the client application will be targeted, and
- develop the expert system (service) and the client system.

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